

# Quantum Machine Learning



**M Dobson**  
**Mentor - Glen Uehara**  
**Faculty Advisor - Professor Spanias**

# Motivation

## What is Quantum Computing?

- Quantum mechanics applied to computation

## Why use Quantum Computing?

- Capable of managing extremely large data sets
- Inherently parallelized
- Thousandfold computation speed increase potential
- Advantages cross over into ML applications

## What are the Challenges?

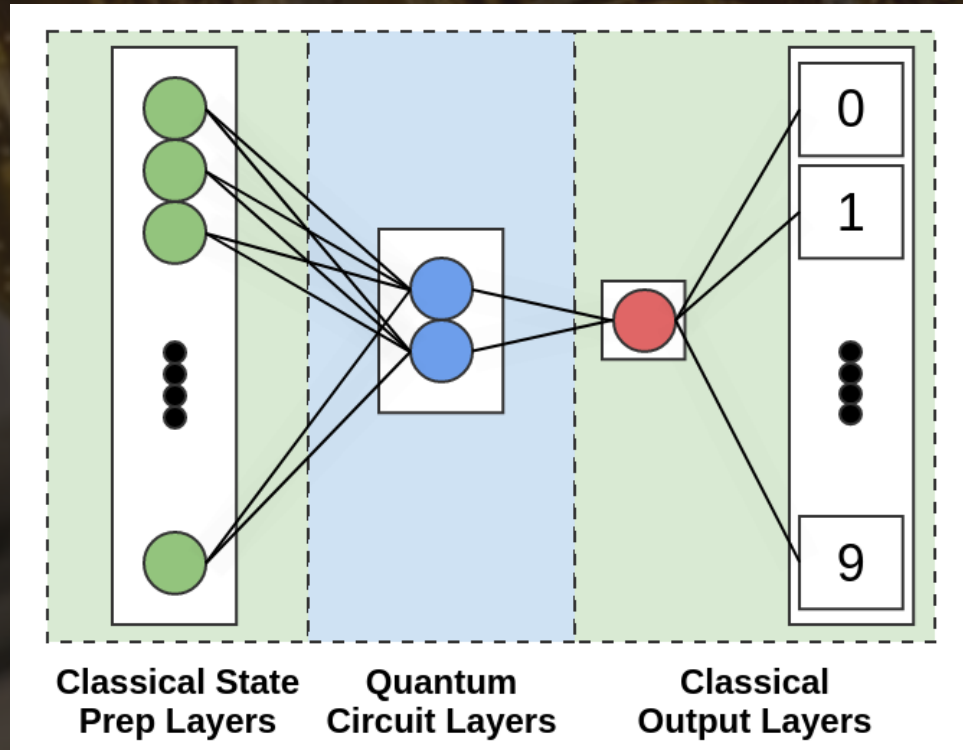
- Execution time is a large barrier
- Increasing precision in terms of qubits adds complexity to several factors

Legacy IBM Quantum Computer



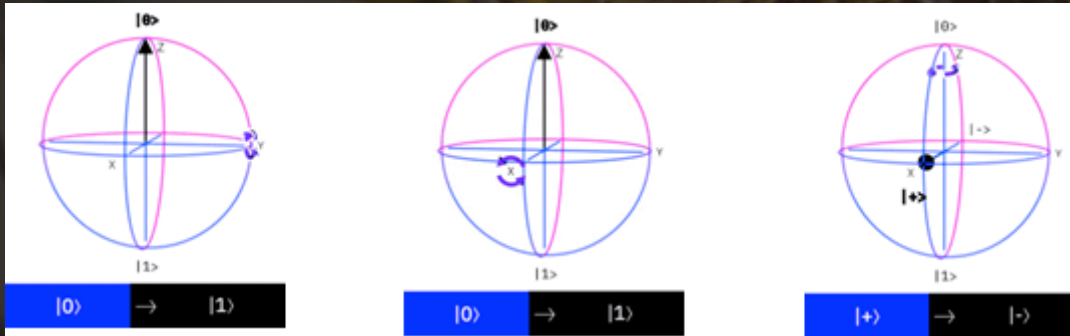
# Hybrid Quantum-Classical Neural Networks

- Uses PyTorch and Qiskit, connected via TorchConnector module
- Classical component can be graphics processor unit (GPU) accelerated (Torch CUDA)

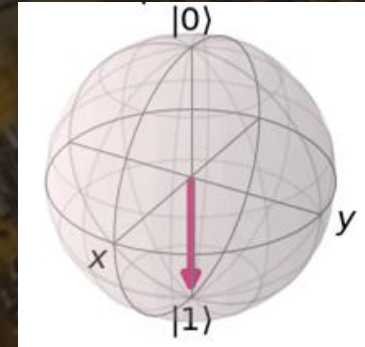


# Quantum Hidden Layers

- Qubits perform gradient descent through rotations around a sphere
- Vector position represents state of the qubit (weights from training)



Rotation gate operations on qubits



Bloch Sphere Representation of a qubit

[https://algassert.com/quirk#circuit=\[\[%22Counting2%22\],\[%22Chance%22,%22Chance%22\],\[\[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22\],\[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22\],\[\[%22E2%80%A2%22,%22X%22\],\[\[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22\],\[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22\]\]\]](https://algassert.com/quirk#circuit=[[%22Counting2%22],[%22Chance%22,%22Chance%22],[[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22],[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22],[[%22E2%80%A2%22,%22X%22],[[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22],[%22id%22:%22Ryft%22,%22arg%22:%22pi%20t%22]]])

# Quantum Simulators

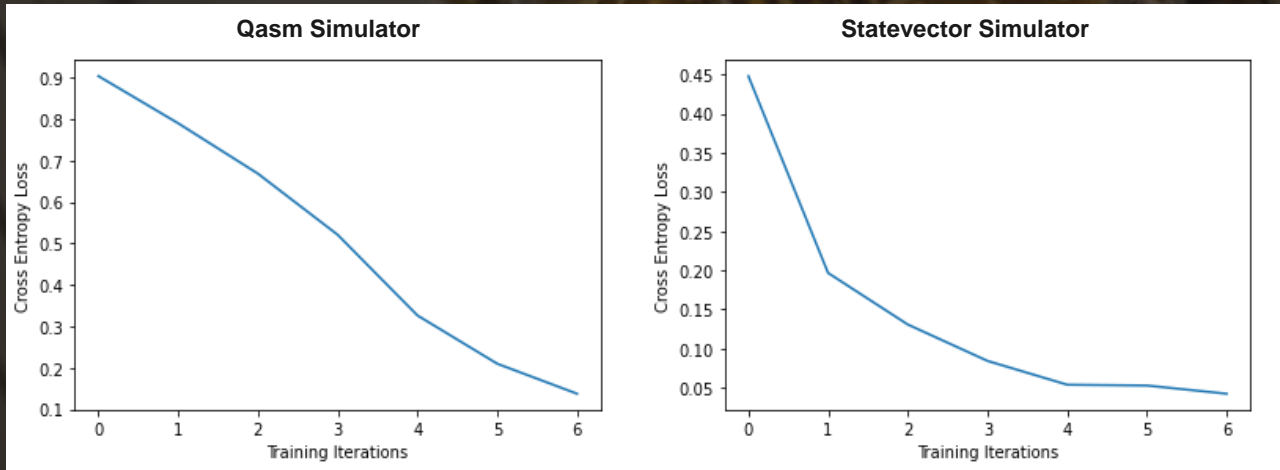
## Simulator Options in Qiskit:

- Qasm - simulates noisy backend system
- Statevector - provides the state vector of the circuit
- Unitary - provides unitary matrix of circuit
- Pulse - simulates pulse schedules to execute directly on hardware channels

Simulator:	Qasm	Statevector
Runtime (min):	14.38	10.44
Accuracy (%):	96-99	99.4

**System Specifications:**  
PopOS 20.10  
Ryzen 9 4900HS  
RTX 2060

## 2 Qubit QNN, 7s vs 1s on MNIST Dataset - Cost Reduction



# Challenges

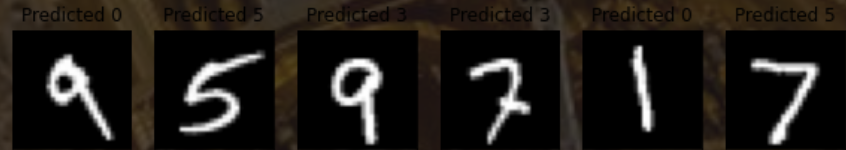
## Accuracy

- Small number of qubits introduces resolution-related noise
- Experimentation suggests as qubit number increases, stability and reliability decrease

## Time

- Most models require several hours to train
- Hybrid nature of QNNs make development difficult
- Have cut time down from ~12+ hours to around 45 minutes

Selection of test results from trained MNIST QNN model



Accuracy and training time for MNIST QNN model

```
Starting epoch 0 for 2 qubits
Training [20.000000%] Loss: 2.5762
Starting epoch 1 for 2 qubits
Training [40.000000%] Loss: 2.3445
Starting epoch 2 for 2 qubits
Training [60.000000%] Loss: 2.3263
Starting epoch 3 for 2 qubits
Training [80.000000%] Loss: 2.3193
Starting epoch 4 for 2 qubits
Training [100.000000%] Loss: 2.3160
Training runtime for two qubits is: 176.34958395560582 min
```

Performance on test data:

Loss: 2.3158

Accuracy: 11.3%

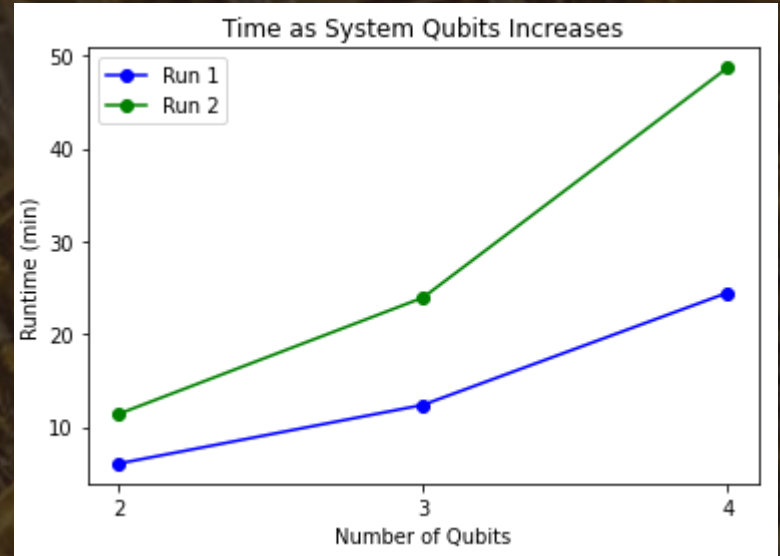
Evaluation time is: 0.259'

# Effects of Higher Qubit Numbers

- Increasing qubits in a simulated environment increases runtime as expected
- Results in simulation vary, but overall pattern is consistent

## Future work

- Fixing issue with evaluation code
- Would like to try 5+ qubits and

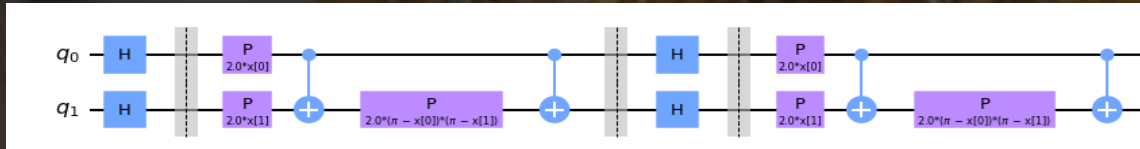


# Quantum Circuit Complexity Reference

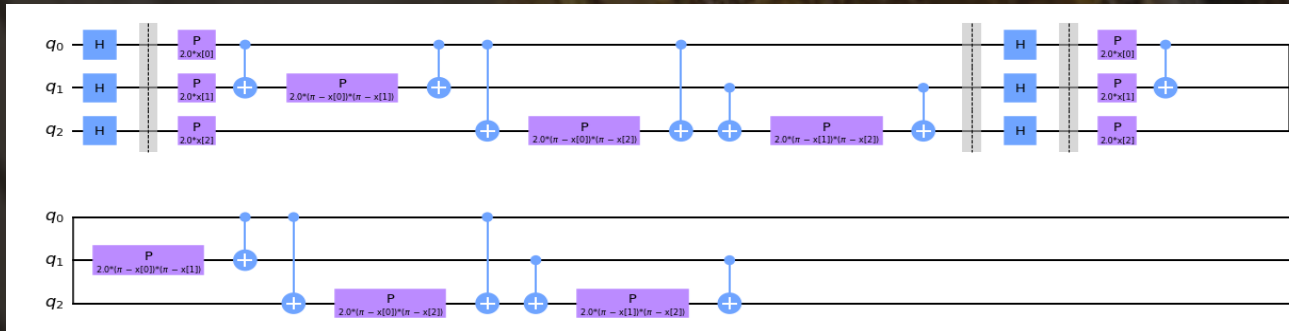
## The quantum circuit:

- Provides abstracted representation of the quantum program logic
- Can increase number of qubits to increase resolution, comes at the cost of error (noise)
- Expected to be solved as technology matures

2 Qubit feature map



3 Qubit feature map





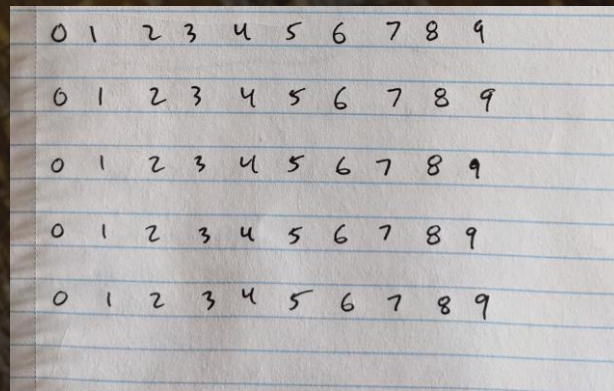
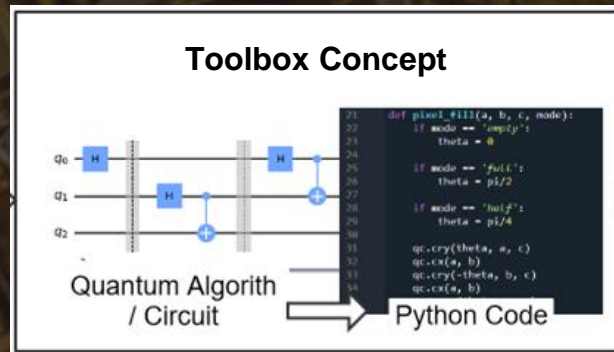
# Concluding Remarks

## Results So Far

- Improved architecture for hybrid QNNs
- Demonstrated functionality on MNIST dataset
- Developed two separate frameworks for handling multi-class datasets on a hybrid network

## Next Steps

- Continue work through independent study in the Fall semester. Will entail:
  - Model improvements
  - Circuit improvements
  - Expansion of models to real-world datasets
  - Tool comparison in regard to complexity of design, execution time, user-friendliness
- Develop handover documentation to pass on the research for future work
- Turn existing code into simple toolbox solutions



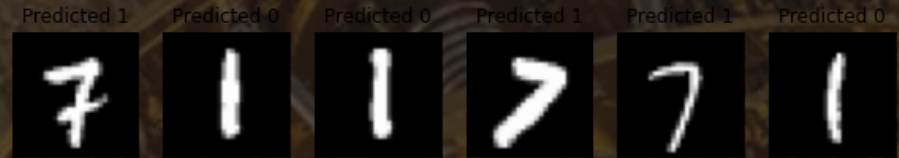
# Sources

- [1] A. Baldominos, Y. Saez, P. Isasi, "A Survey of Handwritten Character Recognition with MNIST and EMNIST" Applied Sciences, 3169;doi:10.3390/app9153169, Aug. 2019,U.
- [2] S. Shanthamallu, A. Spanias, C. Tepedelenioglu, M. Stanley, "A Brief Survey of Machine Learning Methods and their Sensor and IoT Applications" SenSIP Center, School of ECEE, Arizona State University, NXP Semiconductors
- [3] G. Uehara, "Quantum Machine Learning using Quantum Simulation" School of ECEE, Arizona State University
- [4] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. E. Mohamed, H. Arshad, "State-of-the-art in artificial neural network applications: A survey" Heliyon, Volume 4, Issue 11, Nov. 2018, e00938
- [5] B. O. Kaziha "A comparison of Quantized Convolutional and LSTM Recurrent Neural Network Models Using MNIST". International Conference on Electrical and Computing Technologies and Applications, ICECTA 2019 (2019).
- [6] A. Palvanov, Y. Choy "Comparisons of deep learning algorithms for MNIST in real-time environment". International Journal of Fuzzy Logic and Intelligent Systems (2018), 126-134, 18(2)
- [7] S. Y. Simard, D. Steinkraus, J. C. Platt "Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis". IEEE Computer Society, (2003)
- [8] D. Peadaranti "Comparisons of non-linear activation functions for deep neural networks on MNIST classification task". Department of Computer Science, University of Edinburgh, (2018)
- [9] V. P. Ngoc, H. Wiklicky "Tunable Quantum Neural Networks for Boolean Functions" Imperial College London. ArXivID: 2003.14122v2
- [10] E. Grant, M. Bendetti, S. Cao et al "Heirarchical Quantum Classifiers" Quantum Information, (2018), 1-8, 4(1)
- [11] G. Uehara, S. Rao, M. Dobson, C. Tepedelenioglu, A. Spanias "Quantum Neural Network Parameter Estimation for Photovoltaic Fault Detection" IEEE IISA 2021 Conference, SenSIP Center, School of ECEE, Arizona State University

# Results So Far (EXTRA)

## Training on 2 digits

- ❑ High accuracy when comparing only two samples
- ❑ Operates well with simple 2 qubit computers and sims



Performance on test data:

Loss: 0.0565

Accuracy: 99.4%

Evaluation time is: 0.027743311723073323 min

## Training on all 10 digits

- ❑ Lower accuracy and extremely long training time

